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(71) Applicant: SEISMED INSTRUMENTS, INC. [US/US]; 13700 First Avenue North, Minneapolis, MN 55441 (US).

(72) Inventors: ZANETTI, John, M. ; 1690 Bollum Lane, Long Lake, MN 55356 (US). POLIAC, Marius, O. ; 1669 Glenview Court, Arden Hills, MN 55112 (US). KREKELBERG, Daniel, D. ; 9800 69th Avenue North, #114-D, Maple Grove, MN 55369 (US).

(74) Agent: HAMRE, Curtis, B.,; Merchant, Gould, Smith, Edell, Welter & Schmidt, 3100 Norwest Center, 90 South Seventh Street, Minneapolis, MN 55402 (US).

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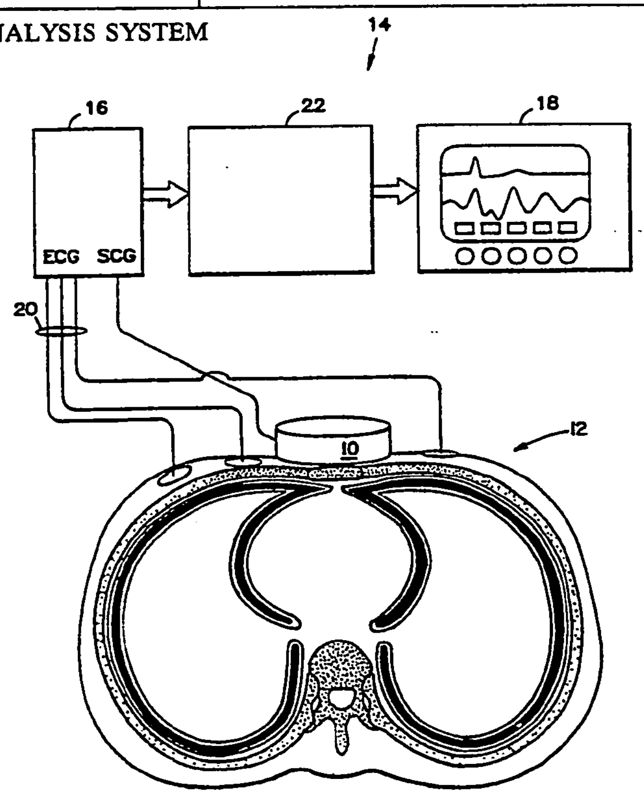
(54) Title: SEISMOCARDIOGRAPHIC ANALYSIS SYSTEM



(57) Abstract

Apparatus for generating a diagnostic display of a patient's seismocardiogram (SCG). The SCG waveform is collected (50) and segmented into wavelets (56). The wavelets are cross-correlated (60-65) and averaged to generate a representative waveform (64). Certain measurements are performed on the waveform and these parameters (68) are multiplied by selected weighting coefficients to generate an advisory diagnosis (76).

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SEISMOCARDIOGRAPHIC ANALYSIS SYSTEM

Background of the Invention

Field of the Invention

The present invention relates to seismocardiography, and more particularly to a non-invasive seismocardiograph system for diagnosing abnormal cardiac function. The system collects, categorizes, averages and analyses the patient's seismocardiogram (SCG) and provides the attending physician with a preliminary and advisory diagnosis based upon a sequence of measurements made upon the collected data.

Description of the Background Art

Seismocardiography is a technique for the non-invasive assessment of the mechanical motion of the heart. In general, compressional waves generated by the mechanical motion of the heart are detected by a seismic transducer from the surface of the patient's chest. The preferred location for the transducer is typically the lower third of the sternum.

U.S. Patent No. 4,989,611 to Zanetti, et al., issued Feb. 5, 1991 discloses a system for the non-invasive assessment of myocardial ischemia through the use of seismocardiography. This patent teaches, *inter alia*, the exclusion of electrically abnormal beats from the collection of SCG data used for diagnostic purposes.

Although seismocardiography has proven to be a reliable and accurate method of assessing the mechanical function of the heart, it has not achieved dominance as a non-invasive diagnostic procedure, in part due to the unfamiliarity with appropriate interpretive technique among physicians/diagnosticians.

Summary of the Invention

In contrast to prior seismocardiographic systems, the present invention formulates a preliminary diagnosis (78) based upon certain measurements made upon collected and processed data.

In operation, patient data is taken under a stress test protocol (50). Simultaneous electrocardiographic

ECG (20) and seismocardiographic SCG (10) data are taken pre-exercise, post-exercise and during recovery from exercise.

The SCG data is broken up into discrete waveform segments (56) which correspond approximately to the mechanical motion of the heart during individual heart-beats. Each of these SCG waveform segments is called a "wavelet" (w1-w6).

Each SCG wavelet is compared with all other wavelets to ascertain their degree of similarity (58). This cross-correlation process is repeated iteratively.

The cross-correlation process categorizes and groups wavelets into families (a-e) based upon intra-family similarity. It has been found through experimentation that as many as ninety percent (90%) of the wavelets will fall into one family (c). A family of highly self-similar wavelets, which contains the majority of all wavelets analyzed is formed and is referred to as the "dominant family of wavelets" (64).

Families of dominant wavelets are extracted for two phases of the stress test. A pre-exercise or baseline dominant family is developed as is a post-exercise dominant family.

Each dominant family set of wavelets is averaged to arrive at a canonical form wavelet which typifies the data collected during the corresponding phase of the stress test. This canonical form wavelet is referred to as the "representative waveform". The representative waveforms generated are displayed to the diagnostician (see 82 and 83,FIG.3 and 84 on FIG.5). Two of the three phases of the stress test are used to generate the advisory diagnosis.

Certain features or points on the representative waveforms can be consistently identified (66). These point are identified on the waveforms and certain measurements are made between points. For example amplitudes are measured and expressed in acceleration

units (g). Slopes are measured and are expressed as acceleration per unit time (g\ms). Time interval between events are also made and expressed in milliseconds (ms).

This measurement and calculation process is referred to as "parameterization" of the representative waveform (68). The resultant times, amplitudes, slopes and ratios are called collectively "parameters", and these are displayed in a hard copy format as shown in FIG. 4.

These parameters are multiplied by certain pre-defined "weighting coefficients" to form "weighted parameters" (70). The weighted parameters are added up and if their collected value tends toward zero, the candidate waveform is likely to have arisen from a healthy heart, while if the sum tends toward unity then the candidate waveform is indicative of a disease state (74).

The advisory diagnosis thus formed, is presented 78 to the diagnostician along with other waveform and parameter information to aid in interpretation by the diagnostician.

Brief Description of the Drawings

Throughout the figures, identical reference numerals refer to identical structural elements, wherein:

FIG. 1 is a schematic view depicting the seismocardiographic analysis system;

FIG. 2 is a schematic plan view of the diagnostic waveforms indicating SCG nomenclature;

FIG. 3 is a panel of data in the format presented to the diagnostician;

FIG. 4 is a panel of data in the format presented to the diagnostician;

FIG. 5 is a panel of data in the format presented to the diagnostician;

FIG. 6 is a schematic presentation showing the segmentation of the SCG data into wavelets;

FIG. 7 is a histogram showing the results of a hypothetical cross-correlation of the schematic data of FIG. 6;

FIG. 8 is a table of parameters along with their identifier code and units of measure;

FIG. 9 is a table of parameter weighting coefficients and their identifier code, as computed by a neural network, presenting values for pre-exercise or baseline; post-exercise, and recovery-from-exercise phases of the stress test value, and;

FIG. 10 is a flow chart depicting program flow for the seismocardiographic analysis system of FIG. 1.

Detailed Description of the Invention

Overview of the Physical System

A wide range of hardware platforms can be used to carry out the invention. FIG. 1 shows an exemplary system which includes a seismocardiographic sensor 10, placed on the chest of the patient 12 to collect SCG data from the patient. In a preferred mode, electrocardiographic data, from ECG leads 20, is collected and supplied to the seismocardiograph 14.

The seismocardiograph 14 itself, is partitioned into computing apparatus 22, signal processing hardware 16, and display structures 18. The computing apparatus collects and processes the SCG and ECG data while the display 18 provide graphic output to the physician in both hard copy and display screen formats. FIG.3,4 and 5 represent hard copy output provided by the machine to the diagnostician.

The preferred seismocardiographic sensor is a ultra-low frequency seismic accelerometer which weighs about one kilogram and which may be conveniently placed on the patients sternum.

Any one of a number of suitable ECG electrode arrays may be used to carry out the invention.

Both the SCG and ECG signals are buffered and isolated and may be filtered using a bandpass filter

having a .3 to 50 Hz. passband. The frequency response should be extended toward DC as much as possible consistent with coupling requirements. Although the high frequency cut off is relatively low, much higher frequency response for the sensor is desired to preserve the fidelity of the SCG waveform. The SCG and ECG data is then converted to digital form at a sampling rate of 250 sample/second. An IBM compatible AT class computer 22 is suitable for data reduction and processing.

Overview of System Operation

In general, the analog ECG and SCG signals are collected from the patient through the signal processing module 16. This data is converted into a digital format and supplied to the computing module 22. This activity corresponds to process 50 shown on FIG. 10.

The first objective of the computing system 16 is to parse the SCG data based on the ECG data and segment the SCG waveform data into wavelets. This object requires elimination of non-sinus beats and the identification of the R-wave peak in the remaining waveform data. This process corresponds to process 52 on FIG. 10.

As shown in FIG. 6 the ECG waveform 24 is scanned and an appropriate collection of rules is applied to determine the locations of R-wave peaks 1 through 6 in the ECG channel data.

It is important to exclude SCG data arising from non-sinus heartbeats. It has been determined that non-sinus beats are so abnormal mechanically, that they degrade the diagnostic potential of the SCG and should be considered noise. Therefore the ECG channel is scanned to exclude all non-sinus beats and to determine the location of the remaining R waves. A variety of ECG beat classification schemes may be used without departing from the scope and spirit of the invention. It is important that the ECG classifier algorithm be conservative and be biased toward incorrect exclusion of beats rather than incorrect inclusion of beats. One

suitable ECG classification methodology suitable for carrying out this invention is depicted in process 54 on FIG. 10.

Next the SCG waveform 26 is cut up into wavelets based upon the position-in-time of the simultaneously recorded electrographic R waves. In general, the R wave peak is identified in the ECG 24 and a time window corresponding to 100% of the measured R to R interval is applied to the SCG waveform. This window is asymmetrical around the R wave peak, and data is collected 20% prior to the R wave peak and 80% after the R wave peak, as shown by wavelet windows w1 through w6 in FIG. 6. Thus, the entire SCG waveform resulting from normally conducted beats is partitioned into wavelets. This process corresponds to 56 in FIG. 10. As shown in FIG. 6 the process 54 excludes premature ventricular contraction event (PVC) 7 and the corresponding SCG data are not folded into the wavelet series, shown in the drawing as 28-33.

The wavelets are next cross-correlated to ascertain their similarity. This corresponds to process 58 in FIG 10. Self-similar wavelets are collected into sets. In general, most wavelets from a given data collection session fall into one class or set, called the dominant family. Classes with a small number of members (less than 25%) are deleted. This corresponds to process 60 on FIG. 10.

The remaining sequence of retained (dominant) wavelets are added and averaged together to form a canonical form wavelet which typifies the waveform taken from a specific patient during a particular phase of a particular stress test. This canonical form wavelet is called the "representative waveform", for the particular case under consideration. This process is depicted schematically in FIG. 7 where wavelet type c dominates, with the largest membership. Line 34 represents the cut off for wavelet types. The sets below the line do not

have sufficient membership to be considered useable sets so they are deleted. In the drawing type b, d and e wavelets are deleted, while wavelet types a and c are combined together to form the representative waveforms. At present the representative waveform of only one family is used for the advisory diagnosis. The wavelets w1 through w6 are mapped into the histogram to show how the histogram is developed. At present any set with less than 25% of the total wavelets is excluded from the representative waveform. These steps correspond to processes 62 and 64 in FIG. 10.

Although cross-correlation of data is well known it must be applied with care to the present data. Relatively brief corruptions of the data due to coughing result in a large number of families with very low membership, while very heavy repetitive respiration can generate a smaller number of more heavily populated families. In general the correlation coefficients are varied to class and reclass the data until about 90% of the wavelets fall into a small (6) number of families. Data which doesn't fit this criteria is suspect, although the apparatus will still generate an advisory diagnosis.

SCG Nomenclature

FIG. 2 shows a schematic representation of simultaneously recorded ECG and SCG data. The electrocardiographic events depicted on the drawing correspond to the P wave 36, the QRS complex 37,38,39, and the T wave 40. In general, the P wave corresponds to the contraction phase of the atria of the heart which forces blood into the ventricles of the heart. The QRS complex arises from depolarization potentials generated by the contraction of the ventricular muscles of the heart. This contraction phase is followed by the T wave which generally represents the repolarization of the muscle tissue of the ventricle.

Through the use of simultaneously recorded ECG's, and echocardiogram data, certain repetitive points can be consistently identified on the SCG wave form set forth in the figure. For example The MC event 42 corresponds to mitral valve closure. The AO event 43 corresponds to the opening of the aortic valve. The RE event 44 corresponds to the rapid ejection of blood through the aorta. The AC event 46 corresponds to the aortic valve closure. The MO event 47 corresponds to the opening of the mitral valve. The RF phase 48 corresponds to rapid ventricular filling. The AS 49 inflection corresponds to the atrial systole. Identification of these wave form features on the fly is done based upon slope and amplitude information. The preferred decision rules applied to the representative waveforms are set forth as follows:

The MC event is the first peak occurring in time after the peak of the electrographic R-wave.

The AO event is the first valley after the MC.

The RE event is the next peak after AO.

The AC event is first peak after the end of the electrographic T-wave. T-wave are notoriously hard to locate due to the low slope. In the absence of successful T-wave detection based upon slope information the approximate T-wave position is defined based on measured R-R interval, the corresponding AC location is defined as a result.

The MO event point is taken as the second valley following the AC event.

The RF event is the next peak after MO.

The AS event is taken as the last peak before the onset of the Q-wave in the ECG.

The SCG waveform is scanned according to these rules to locate these points or events on the SCG, and corresponds to process 66 on FIG. 10.

The various time intervals between events as well their amplitudes and slopes are also measured, these are referred to as measured parameters.

A number of quantitative parameters may be computed from these seismocardiographic and electrocardiographic events. These parameters include: the Q to AC time interval, the Q to RE time interval. The RE to AC time interval, the AC to RF time interval, the MC-AO amplitude, the AO-RE amplitude, the RF amplitude, the AS amplitude, as well as the MC-AO slope, the AO-RE slope and the MO-RF slope. These computed parameters are called the calculated parameters.

These calculated parameters and measured parameters taken together are simply called the parameters. Certain of these quantitative parameters can be used to calculate traditional measures of cardiac performance, including the pre-ejection period (PEP), the left ventricular ejection time (LVET), as well as the ratio of PEP to LVET.

These and other non-traditional parameters can be used for developing the advisory diagnosis, at present the most useful parameter set known is set forth as the table of FIG.8. The parameter set disclosed is all defined within substantially one beat of the heart. In other words, this illustrative and preferred parameter set is draw from underlying cardiac events occurring within one cycle of heart action. The formation of the parameter set corresponds to process 68 on FIG. 10.

Neural Net Background

A neural network is used to create the weighting coefficients used by the computation system 14 for the advisory diagnosis.

Multi-layered neural networks are an emerging supercomputer technology which utilizes learning-by-back-propagation to categorize or classify certain patterns. This technology has been applied to bond rating, mortgage application evaluation, protein structure

determination, backgammon playing and hand-written digit determination. Neural network analysis can take the place of traditional statistical analysis of data to determine weighing coefficients, and is especially useful were training by example is preferred to programmed pattern analysis.

As used herein, a neural network is a system that produces an output vector that is a function of an input vector. The mapping function between the input and output vectors is learned. In general, a neural network will include a number of processing elements, called neural units, arranged in layers. Interconnections are made between units in the successive layers. A typical network has an input layer, an output layer, and one or more hidden layers in between them. The hidden layer facilitates solutions to highly non-linear problems. Each of the processing units functions in a way which is analogous to a biological neuron.

The original theoretical approaches toward understanding neural networks were based upon the idea that when two neurons in the brain are active, the connection or synapse between them is strengthened. One early rule, developed by D. O. Hebb is described in his book, "The Organization of Behavior", Wiley, 1949. The Hebbian rule states that when two neurons are firing simultaneously, an association link between them is strengthened. Accordingly, the next time either of the two neurons fires, the other one is more likely to fire as well. Although the Hebbian rule is useful qualitatively, it fails to explain the learning process. For example, under a Hebbian rule, the connection strengths between neurons grow without bound, or if maximums are placed upon connection strengths, these maximums are always reached. In 1962, Frank Rosenblatt introduced the Perceptron model in his book, "Principals of Neural Dynamics", Spartan, 1962. The Perceptron model includes input, hidden, and output layers consisting of

processing elements. An input stimuli presented to the input layer provides information to the hidden layer. In a similar fashion, the hidden layer provides information to the output layer. In the Perceptron model, all the learning takes place at the output layer. Under the Perceptron model, many problems have been experimentally and mathematically shown to be representable by connection strengths between layers.

In operation, the Perceptron model modifies the strengths of weighted connections between processing elements to learn an appropriate output vector or response, corresponding to a particular input vector. The modification of the connection weights occurs when an incorrect output response is given. The modification of the weight is done on an interative basis, and changes the amount, or rate of transfer, of information from the input layer to the output layer, so that eventually, the appropriate output response will be provided. In retrospect, the Perceptron system is now understood as unable to properly adjust more than one layer of modifiable weights. Based upon this fact, it was predicted that no learning mechanism for a multiple layer system with modifiable weights was possible because none existed (Minsky & Pappert, 1969 in "Perceptron"). However, the more recent development of the "Back Propagation" algorithm as set forth in "Parallel Distributed Processing, the Microstructure of Cognition", Rumelhart, Hinton and Williams, MIT Press, 1986, has resulted in the development of multiple layer adaptive learning neural networks. Like the Perceptron model, the idea of errors is introduced to correct or teach the machine to recognize a pattern. However, in a back propagation system, at each output processing element of the network, the error is quite easily realized, and this error is used to modify the strength of the connection between the processing element and the output processing element. This process permits the

allocation of an error value to hidden level elements, and permits the assignment of weight coupled to the hidden processing elements to be adjusted. However, most neural network algorithms, such as the back propagation algorithms, are computation intensive and require supercomputer capacity to efficiently explore pattern learning processes. However, once the weighing coefficients are determined, they may be utilized by substantially simpler computational machines to apply a learned response to new data sets or test cases.

Computation and Use of the Weighing Coefficients

The SCG data taken from a specific patient is called a "case". Fifty seven cases of patients with disease, and fifty seven cases of patients without disease were used to train a neural network.

Each one of the fifty seven cases was prepared for the neural network by parameterizing each of the three representative waveforms collected for the case. The specific parameters formed are set forth in the table of FIG. 8. Thus each case was represented by 48 parameters. This large group of parameters was supplied to a multilayered neural network simulator called BigNet, running a supervised learning back propagation algorithm on a Cray 2 supercomputer. A correction coefficient of (e=.1) resulted in minimal inter-iteration jumps in weighting. The output layer consisted of one node, producing a value of one, for the diseased state and a value of zero for the healthy state. As the result of training, the neural net selected weighing coefficients for the parameters as shown in the table of FIG. 9.

The table of FIG. 9 reflects the relative importance of the various parameters. In general, coefficients which are large, correlate strongly with heart disease in the learning set. For example, parameters p5,p7 and p14 are the most significant parameters of those tested.

The optimal network for generating weighting coeffi-

cients and the best parameters for presenting the cases are not intuitively obvious. Networks, for example, can over learn which results in 100% sensitivity and specificity on the learning set but very poor performance on the test set data.

It is expected that weighting coefficients presented here will be modified and optimized as additional cases become available for analysis. It can also be anticipated that other effective parameters will be uncovered. For this reason the parameter choice and weighting values presented herein should not be taken as limiting but rather as illustrative of the invention.

In use the apparatus collects the SCG and ECG data from the patient. Appropriate representative waveforms are formed for both the pre-exercise and the post exercise phases of the stress test and parameterized in accordance with FIG. 8. The parameters are multiplied by the appropriate weighting coefficient drawn from the table of FIG. 9 resulting in a "weighted parameter". This corresponds to the process 70 on FIG. 10.

The collection of the several weighted parameters is summed and multiplied by an determined "offset". The offset for the weighting coefficients presented in FIG. 9 is (w=.7241). The application of the offset corresponds to the process 72 in FIG. 10.

The summation and multiplication process results in the generation of a number which lies between unity (1) and zero (0). Unity indicates disease with high confidence and zero represents disease free with high confidence. Intermediate values indicate varying degrees of indeterminacy or "confidence". This process generates an "interpretive number", and corresponds to process 74 as shown on FIG. 10.

The theory and process of diagnostic stress test seismocardiography, relies on comparisons between the pre-exercise or baseline SCG data with post exercise SCG data to determine if stress induced ischemia has altered

the wall motion of the heart. Since the interpretation process is applied to pre-exercise and to post-exercise waveforms the underlying waveform comparison is inherently made.

This interpretive number is mapped onto the diagnostic display as "abnormal"(1-.7), "borderline abnormal"(.7-.6), "inconclusive"(.6-.4), "borderline normal"(.4-.3) and "normal"(.3-0.0). This mapping operation folds the confidence factor into the generation of the advisory diagnosis. This corresponds to the process 74 on FIG. 10. Process 76 generates the hard copy shown in FIGS. 3, 4 and 5. The advisory diagnosis 78 is displayed in one panel of the display, as shown on FIG. 4.

Twenty cases of SCG data taken from patients with coronary artery disease and twenty cases from patients without known coronary artery disease were used to test the initial neural network. Testing of the neural network is a process similar to the data interpretation processes carried out by the diagnostic system disclosed. The testing process is carried out by parameterizing cases that have not been used for training. The network applied the previously computed weighting coefficients to the parameterized data in a fashion analogous to the method performed by the diagnostic apparatus, and in a similar fashion the net an interpretive number. This advisory diagnosis is graded by comparing it with the known disease factors for the test cases. This grading is done on a "sensitivity " and "specificity" basis.

Sensitivity is the ability to predict disease in patients with disease. It can be computed as the ratio of "true positive" to the sum of "true positive" and "false negatives". Specificity refers to the ability to predict wellness. It is taken as the ratio of "true negatives" to the sum of "true negatives" and "false positive". The best performances based upon neural net calculated weighting coefficients was 85% sensitivity

and 75% specificity, which exceeds the performance of the best human readers.

WE CLAIM:

1. Seismocardiographic apparatus for collecting (16) cardiac information from a patient's body, and for displaying (18) an advisory diagnosis derived from said cardiac information to a diagnostician comprising:

compression wave transducer means (10), adapted for coupling to the external surface of said patient's body (12), for collecting time series compression wave information resulting from the motion of said patient's heart, and for producing seismic waveform data;

segmenting means (56) for partitioning said seismic waveform data into a plurality of wavelets;

cross-correlation means (58) for collecting similar ones of said wavelets into sets where set members have similar shape, and for generating a set of representative waveforms;

event extraction means (66) for identifying event locations within said representative waveforms;

parameter measuring means for collecting parameter set data from said representative waveforms and for generating a parameter data set (68);

weighting means for applying a weighting coefficient to each corresponding parameter of said parameter set and for generating a set of weighted parameters (70);

interpretation means for mapping said set of weighted parameters into an advisory diagnosis (72, 74).

2. A method, performed by a machine, to form a preliminary and advisory diagnosis (76) of a disease condition comprising the steps of:

a) collecting physiologic time series data (50);

b) parameterizing said time series data which transforms said data into a set of parameters (68);

c) weighting said parameters by applying a predefined set of weighting coefficients to each of said parameters, forming a set of weighted parameters (70);

d) summing said weighted parameters to form an interpretive number indicative of the presence of disease underlying said physiologic time series data (72).

3. Apparatus for detecting a disease condition in a patient comprising:

compression wave sensor means (10) for collecting a physiologic waveform representing time series of patient data;

processing means (22) for parameterizing said time series data and for generating a sequence of parameters;

weighting means (22) for applying a set of predefined weighting coefficients to said parameters and for generating a set of weighted parameters;

computing means (22) for scaling and transforming said weighted parameters into a diagnostic decision space.

4. A method of generating weighting coefficients (FIG. 9) for use in a seismocardiographic analysis system, comprising the steps of:

collecting seismocardiographic data corresponding to a diseased state and corresponding to a non-diseased state;

parameterizing said data, generating parameterized data;

presenting said parameterized data to a multi-layer neural network for back-propagation supervised learning;

collecting weighting coefficients from said network after a fixed number of network iterations.

5. A method of formulating an advisory diagnosis of a patient's disease state, comprising the steps of:

a) collecting electrocardiographic and seismocardiographic time series data from said patient (50);

b1) parameterizing said time series data by locating at a plurality of events,

wherein said events are selected from the group consisting of:

electrographic, R-wave events;

seismocardiographic, MC events, AO events, RE events, PE events, AC events, MO events, RF events, AS events;

b2) parameterizing said time series data by making a plurality of measurements,

wherein said measurements are selected form the group consisting of:

the Q to AC time, the PEP time, the LVET time, the ratio of PEP to LVET, the MC to AO amplitude, the MC to AO slope, the AO to RE amplitude, the AO to RE slope, the ratio of AO to RE slope divided by the MC to AO slope, the sum of the AO to RE slope and the MC to AO slope, the Q to RE time, the AC to Q time, the AC to RF time, the MO to RF amplitude, the MO to RF slope, the AS amplitude,

c) weighting said parameters by applying a predefined set of weighting coefficients to each of said parameters, forming a set of weighted parameters (70);

d) summing said weighted parameters to form an interpretive number indicative of the presence of disease underlying said physiologic time series data (72).

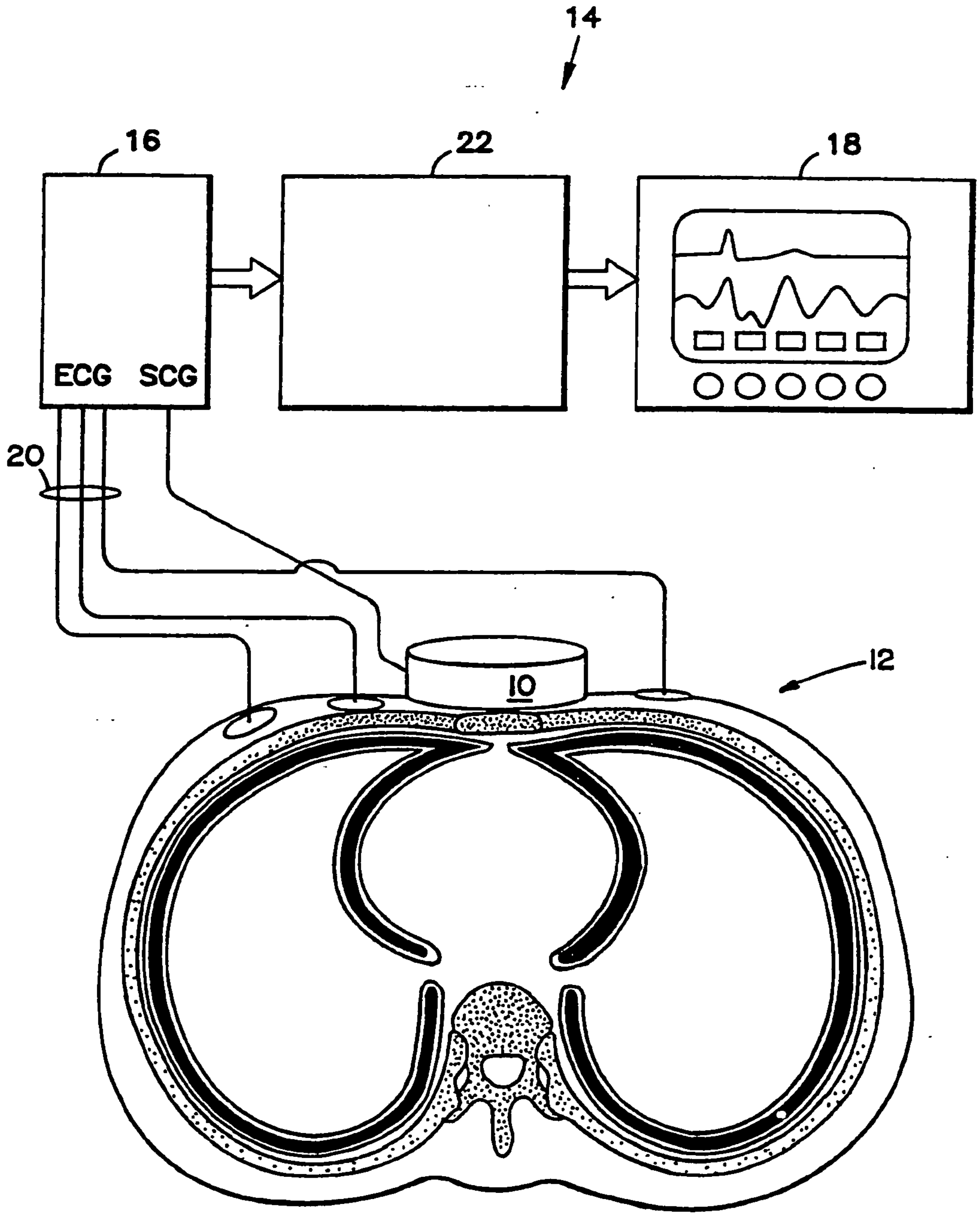
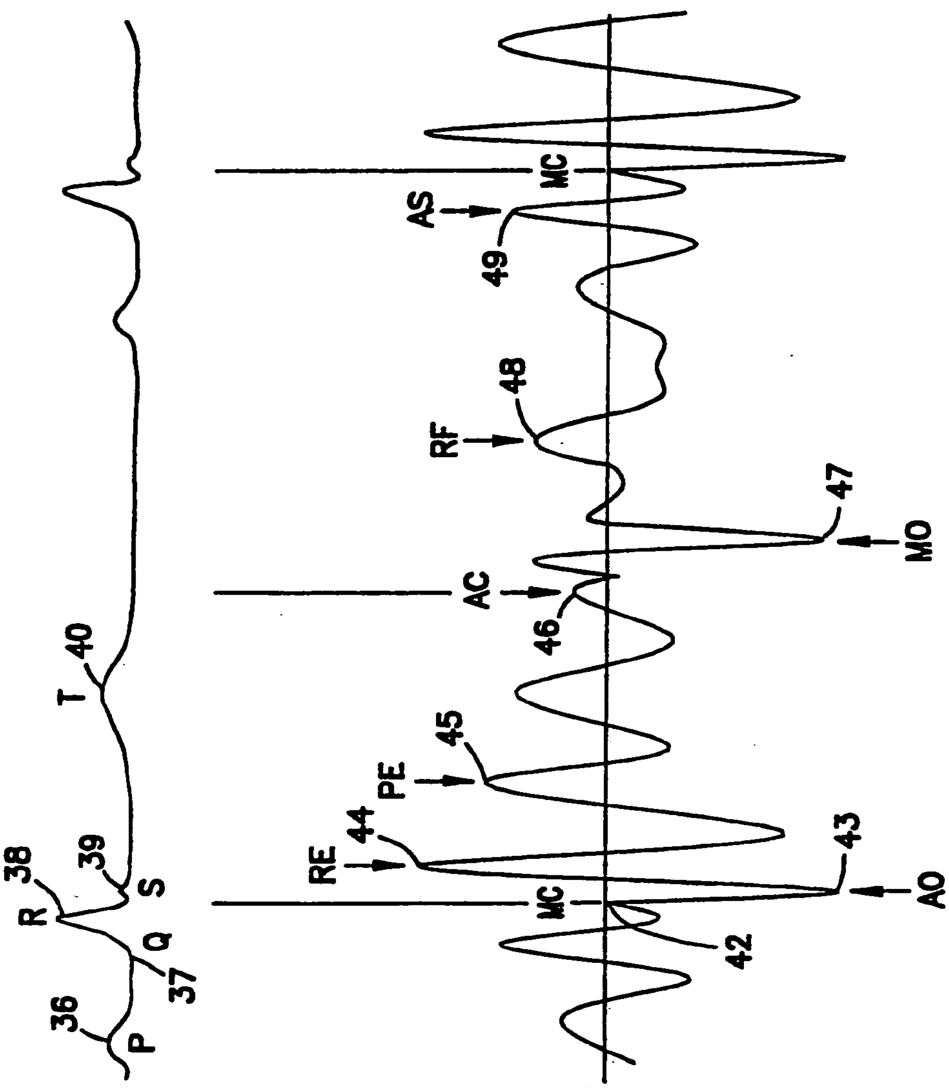


FIG. 1

FIG. 2



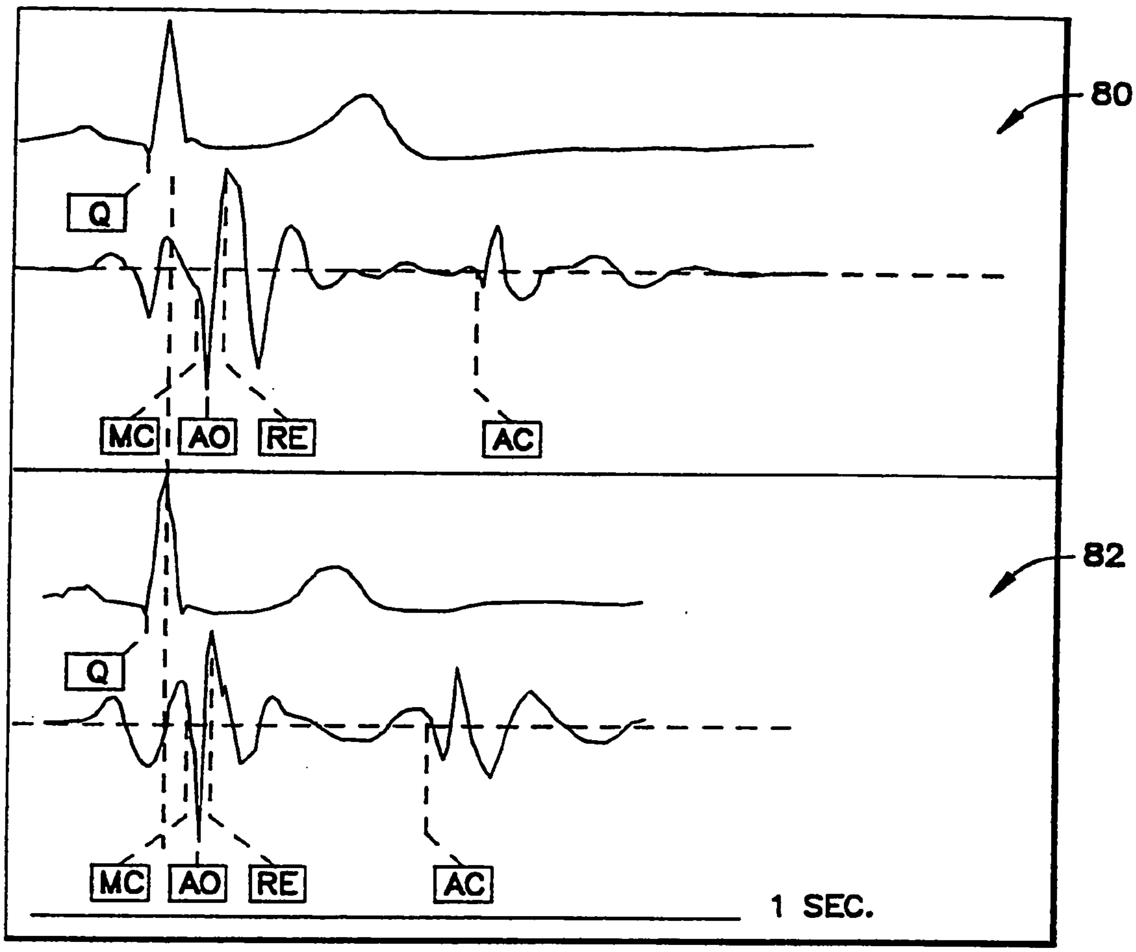


FIG. 3

PARAMETERS	MEASURED RESULTS	NORMAL RANGE
AORE / MCAO AMP AORE / MCAO SLP	POSTEX / BASE = 0.617 POSTEX / BASE = 1.080	

PARAMETER ANALYSIS INDICATES ABNORMAL.

78

BASELINE SYSTOLIC INTs	MEASURED RESULTS	MEASURED NORMALIZED	NORMAL RANGE
TOTAL SYS	460 MS	443 MS	409–439MS
PEP	116 MS	115 MS	96–120MS
LVET	344 MS	326 MS	304–330MS
PEP / LVET	0.34		.25–.43

POSTEXERCISE SYSTOLIC INTs	MEASURED RESULTS	MEASURED NORMALIZED	NORMAL RANGE
TOTAL SYS	396 MS	421 MS	
PEP	96 MS	96 MS	
LVET	300 MS	325 MS	
PEP / LVET	0.32		

FIG. 4

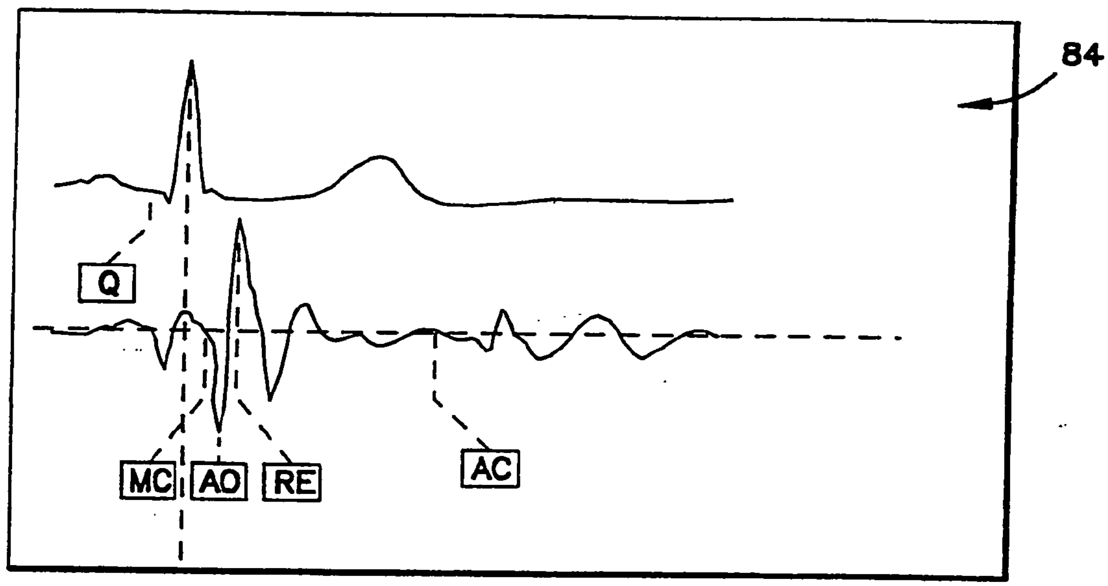
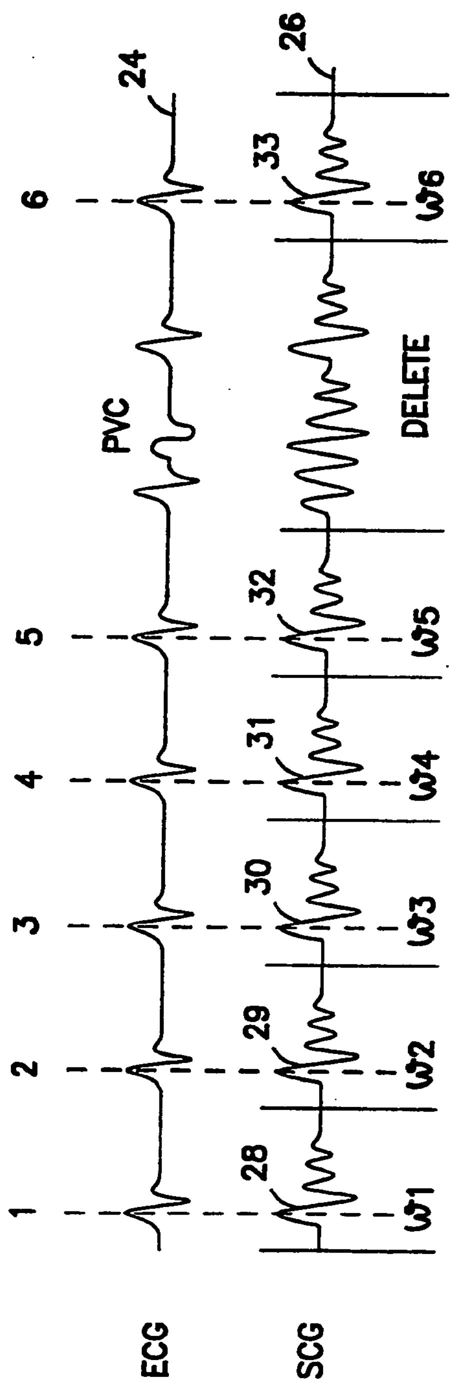


FIG. 5

FIG. 6


ECG
SCG
1
2
3
4
5
6
24
26
28
29
30
31
32
33
PVC
DELETE
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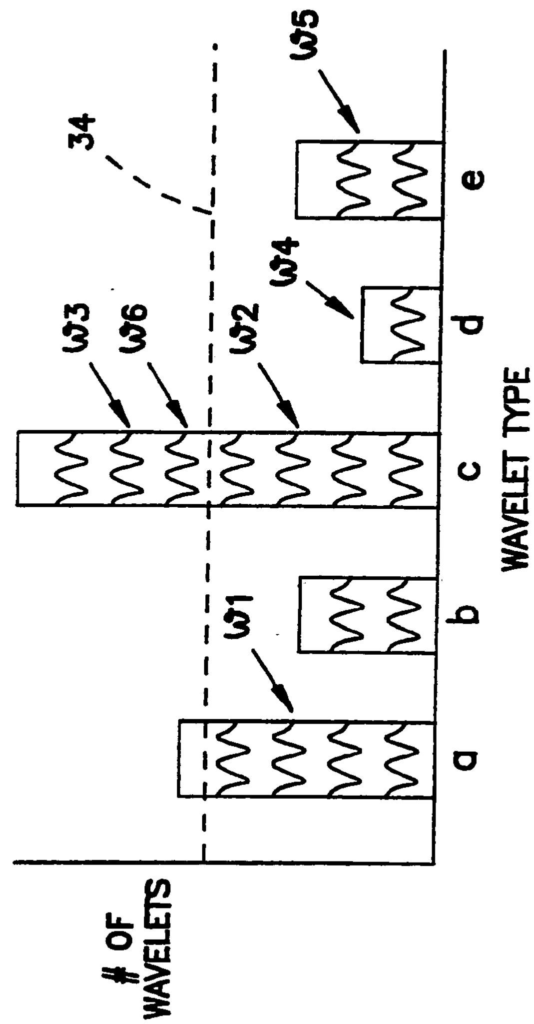
w2
w3
w4
w5
w6

FIG. 7


OF WAVELETS
WAVELET TYPE
a
b
c
d
e
34
w1
w2
w3
w4
w5
w6

CODE	DESCRIPTION	UNITS
P1	SYSTOLIC INTERVAL: Q TO AC	msec
P2	PRE-EJECTION PERIOD	msec
P3	LEFT-VENTRICULAR EJECTION TIME	msec
P4	PRE-EJECTION PERIOD / LEFT-VENTRICULAR EJECTION TIME	
P5	MC TO AO AMPLITUDE	g
P6	MC TO AO SLOPE	g/msec
P7	AO TO RE AMPLITUDE	g
P8	AO TO RE SLOPE	g/msec
P9	AO TO RE SLOPE / MC TO AO SLOPE	
P10	AO TO RE SLOPE + MC TO AO SLOPE	g/msec
P11	Q TO RE INTERVAL	msec
P12	DIASTOLIC INTERVAL: AC TO Q	msec
P13	AC TO RF INTERVAL	msec
P14	MO TO RF AMPLITUDE	g
P15	MO TO RF SLOPE	g/msec
P16	AS WAVE AMPLITUDE	g

FIG. 8

CODE	BASELINE	POST EXERCISE	RECOVERY
P1	2.7	7.6	−3.5
P2	4.3	30.0	−0.1
P3	−0.8	−8.4	−4.0
P4	−8.0	−20.3	9.2
P5	−37.2	8.8	6.9
P6	−1.4	−8.8	−3.6
P7	29.0	−31.0	−3.5
P8	−6.4	15.4	27.9
P9	−6.7	4.6	3.7
P10	−5.4	3.5	16.5
P11	−7.7	−10.7	6.0
P12	7.9	13.5	−10.8
P13	−0.3	−8.1	1.4
P14	10.2	19.2	29.1
P15	−3.9	−24.1	−42.2
P16	5.4	16.2	−9.5

FIG. 9

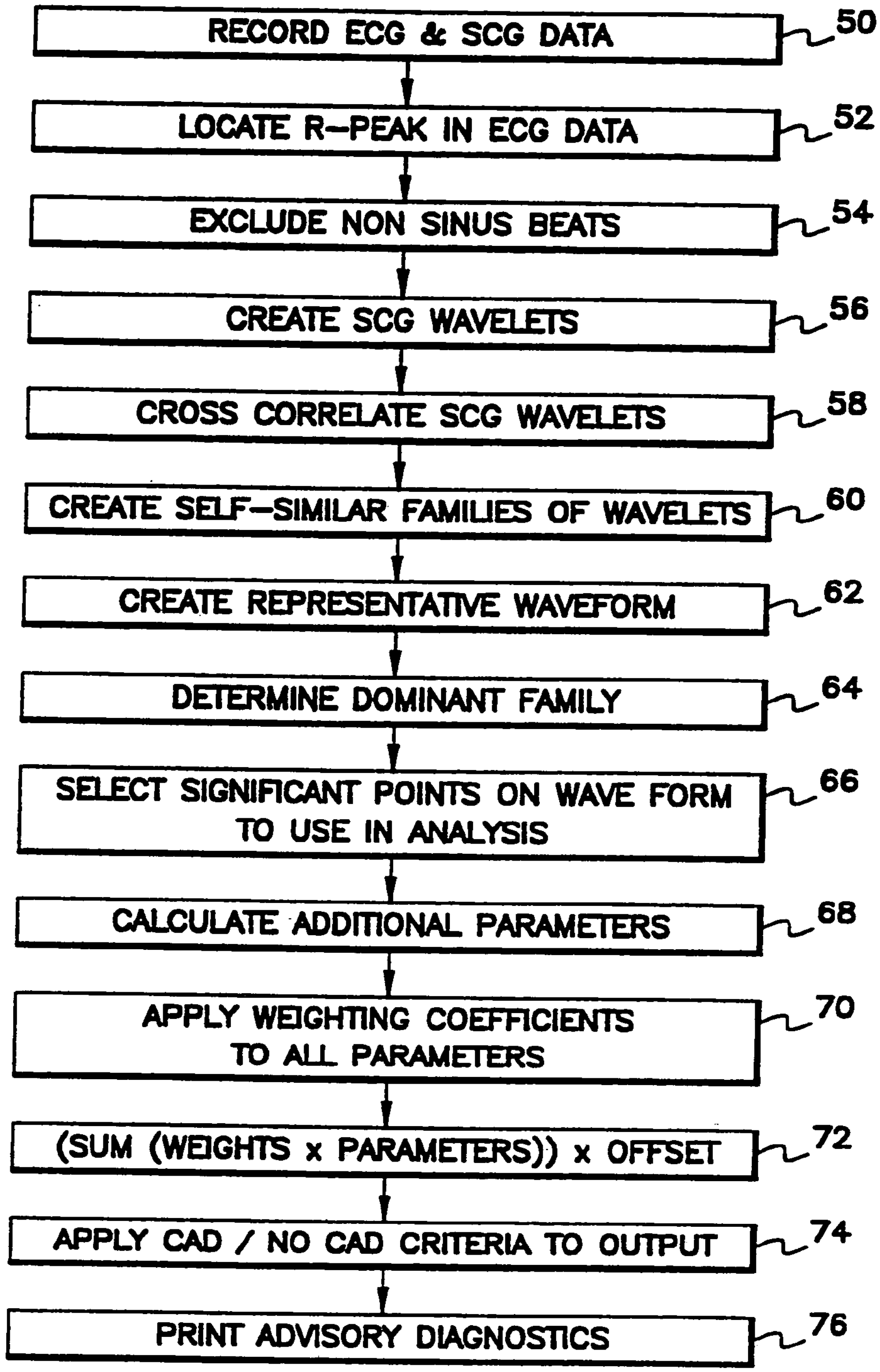

RECORD ECG & SCG DATA
50
LOCATE R-PEAK IN ECG DATA
52
EXCLUDE NON SINUS BEATS
54
CREATE SCG WAVELETS
56
CROSS CORRELATE SCG WAVELETS
58
CREATE SELF-SIMILAR FAMILIES OF WAVELETS
60
CREATE REPRESENTATIVE WAVEFORM
62
DETERMINE DOMINANT FAMILY
64
SELECT SIGNIFICANT POINTS ON WAVE FORM TO USE IN ANALYSIS
66
CALCULATE ADDITIONAL PARAMETERS
68
APPLY WEIGHTING COEFFICIENTS TO ALL PARAMETERS
70
(SUM (WEIGHTS x PARAMETERS)) x OFFSET
72
APPLY CAD / NO CAD CRITERIA TO OUTPUT
74
PRINT ADVISORY DIAGNOSTICS
76

FIG. 10

INTERNATIONAL SEARCH REPORT

International Application No PCT/US 92/03934

I. CLASSIFICATION OF SUBJECT MATTER (if several classification symbols apply, indicate all)[6]

According to International Patent Classification (IPC) or to both National Classification and IPC

Int.Cl. 5 A61B7/04; G06F15/20

II. FIELDS SEARCHED

Minimum Documentation Searched[7]

Classification System	Classification Symbols
Int.Cl. 5	A61B ; G06F

Documentation Searched other than Minimum Documentation to the Extent that such Documents are Included in the Fields Searched[8]

III. DOCUMENTS CONSIDERED TO BE RELEVANT[9]

Category °	Citation of Document, [11] with indication, where appropriate, of the relevant passages [12]	Relevant to Claim No.[13]
X	EP,A,0 329 356 (WAYNE STATE UNIVERSITY) 23 August 1989 see column 3, line 32 - column 12, line 49; figures	2
Y		1,3-5

Y	US,A,4 989 611 (ZANETTI ET AL.) 5 February 1991 cited in the application see column 6, line 65 - column 18, line 23; figures	1,3-5
A		2

	-/--	

° Special categories of cited documents : [10]

"A" document defining the general state of the art which is not considered to be of particular relevance

"E" earlier document but published on or after the international filing date

"L" document which may throw doubts on priority claim(s) or which is cited to establish the publication date of another citation or other special reason (as specified)

"O" document referring to an oral disclosure, use, exhibition or other means

"P" document published prior to the international filing date but later than the priority date claimed

"T" later document published after the international filing date or priority date and not in conflict with the application but cited to understand the principle or theory underlying the invention

"X" document of particular relevance; the claimed invention cannot be considered novel or cannot be considered to involve an inventive step

"Y" document of particular relevance; the claimed invention cannot be considered to involve an inventive step when the document is combined with one or more other such documents, such combination being obvious to a person skilled in the art.

"&" document member of the same patent family

IV. CERTIFICATION

Date of the Actual Completion of the International Search	Date of Mailing of this International Search Report
28 AUGUST 1992	09. 09. 92
International Searching Authority	**Signature of Authorized Officer**
EUROPEAN PATENT OFFICE	CHEN A.H.

1

III. DOCUMENTS CONSIDERED TO BE RELEVANT (CONTINUED FROM THE SECOND SHEET)

Category °	Citation of Document, with indication, where appropriate, of the relevant passages	Relevant to Claim No.
X	BIOMEDIZINISCHE TECHNIK. vol. 35, no. 11, November 1990, BERLIN DE pages 271 - 279; BARSCHDORFF ET AL.: 'Phonographische Diagnosehilfe bei Herzfehlern unter Verwendung neuronaler Netze.' see the whole document	2
A		1,3-5
A	INTERNATIONAL NEURAL NETWORK CONFERENCE. vol. 1, July 1990, pages 137 - 140; ZHU ET AL.: 'Training neural networks for ECG feature recognition.' see the whole document	1-5
A	US,A,4 905 706 (DUFF ET AL.) 6 March 1990 see column 2, line 34 - column 7, line 28; figures	1-5

ANNEX TO THE INTERNATIONAL SEARCH REPORT ON INTERNATIONAL PATENT APPLICATION NO. US 9203934 SA 60571

This annex lists the patent family members relating to the patent documents cited in the above-mentioned international search report. The members are as contained in the European Patent Office EDP file on
The European Patent Office is in no way liable for these particulars which are merely given for the purpose of information. 28/08/92

Patent document cited in search report	Publication date	Patent family member(s)		Publication date
EP-A-0329356	23-08-89	JP-A-	2005925	10-01-90
		US-A-	5092343	03-03-92
US-A-4989611	05-02-91	AU-B-	617968	05-12-91
		AU-A-	3523689	22-02-90
		EP-A-	0357275	07-03-90
		JP-A-	2107228	19-04-90
US-A-4905706	06-03-90	JP-A-	2001217	05-01-90

For more details about this annex : see Official Journal of the European Patent Office, No. 12/82